Synopsis of

A UNIFIED FRAMEWORK FOR BLIND RESTORATION OF BLURRED BARCODE IMAGES

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Contents

Sr. No.	Topic	Page No.
1.0	Introduction	1
	1.1 Image Degradation Model	1
	1.2 Blur Model	1
	1.2.1 Motion Blur	1
	1.2.2 Defocus Blur	2
	1.2.3 Combined Blur	2
	1.3 Blind Image Restoration	2
2.0	Literature Review	2
3.0	Research Motivations and Contributions	5
4.0	Description of the Research Work	6
	4.1 Blur Detection	7
	4.2 Blur Type Recognition	8
	4.3 Blur Parameter Estimation	9
	4.3.1 Motion Blur Estimation	9
	4.3.2 Defocus Blur Estimation	9
	4.3.3 Combined Blur Estimation	10
	4.4 Image Deconvolution	10
5.0	Conclusion	10
6.0	List of Publications	11
7.0	Proposed Chapters	12
	Bibliography	12

1. Introduction

Use of barcodes has grown enormously for encoding of machine understandable information. Information about a product such as description and price can be easily accessed with the use of a barcode laser scanner. After laser scanning technology came into practical use, many efforts have been paid to barcode reading through laser scanners (Joseph, and Pavlidis, 1994). However, the biggest disadvantage of the laser barcode readers is their lack of mobility, because most of the time, they can only be used together with the corresponding point of sale (POS) machines. With the availability of camera devices, attention is being paid to developing barcode reading technology on these devices using barcode images (Guo et al., 2002). However, Barcode images normally are prone to deterioration due to a number of degradations (Yang et al., 2012). Image degradation generally occurs due to transmission channel error, camera defocus, atmospheric turbulence, relative object-camera motion, etc. Such degradations are unavoidable while a barcode is captured through a camera. As degraded images are having less scientific values, restoration of such images is extremely essential. Image blurring is often a major factor influencing the performance of a barcode recognition system (Selim, 2004).

1.1 Image Degradation Model

The image degradation model for linear shift invariant (LSI) systems can be expressed as (Gonzalez and Woods, 2002)

$$g(x,y) = f(x,y) * h(x,y) + \eta(x,y) \tag{1.1}$$

where $g(x,y), f(x,y), h(x,y)$ and $\eta(x,y)$ are the degraded image, original image, point spread function (PSF) that caused the degradation and the additive noise respectively in spatial domain. Here, $*$ is the convolution operator. In frequency domain, equation (1.1) can be written as

$$G(u,v) = F(u,v)H(u,v) + N(u,v) \tag{1.2}$$

where $G(u,v)$, $F(u,v)$, $H(u,v)$ and $N(u,v)$ are the degraded image, original image, degradation function and the additive noise respectively in frequency domain.

1.2 Blur Model

Blur is an artefact that occurs in images due to irregularities in image acquisition. Blurs are treated as low pass filters which smoothes out the abrupt changes in the gray level of an image. An image may be blurred in various ways including motion blur, out-of-focus blur, atmospheric turbulence blur etc.

1.2.1 Motion Blur

The point spread function (PSF) for uniform linear motion blur is (Lokhande et al., 2006)

$$h_m(x,y) = \begin{cases} \frac{1}{L} \; if \; \sqrt{x^2+y^2} \le \frac{L}{2} \; and \; \frac{x}{y} = -\tan\theta \\ 0 \qquad \text{otherwise} \end{cases} \tag{1.3}$$

where L and θ are the motion length and angle respectively.

1.2.2 Defocus Blur

The out of focus blur caused by a system with circular aperture can be modeled as a uniform disk with radius R as (Addiati et al., 2009; Joshi, 2014)

$$h_d(x,y) = \begin{cases} \dfrac{1}{\pi R^2} & if\ \sqrt{x^2+y^2} \leq R \\ 0 & \text{otherwise} \end{cases} \tag{1.4}$$

1.2.3 Combined Blur

In the case where both out-of-focus blur and motion blur are present in the same image, the combined (or simulateneous) blur degradation model is (Favaro et al., 2004; Liu and Zhao, 2011)

$$g(x,y) = f(x,y) * h_d(x,y) * h_m(x,y) + \eta(x,y) \tag{1.5}$$

Since convolution is associative, so combined blur PSF can be obtained as convolution of two blur functions as

$$h(x,y) = h_d(x,y) \ * \ h_m(x,y) \tag{1.6}$$

where $h_d(x,y)$, $h_m(x,y)$ are point spread functions for motion defocus and blur respectively and $*$ is the convolution operator.

1.3 Blind Image Restoration

The field of image restoration (sometimes referred to as image deblurring or image deconvolution) is concerned with the estimation of the original image from a blurred and noisy one (Sungchan and Gyeonghwan, 2014). The methods which do not use prior information about the blur, known as blind restoration methods. Blind restoration methods follow one of the following two approaches (Campisi and Egiazarian, 2006; Marais and Steyn, 2007)

1. First estimate the PSF and then use a classical deconvolution technique such as Wiener filtering to restore the image (Lokhande et al., 2006; Dash et al. 2009; Chandrakala et al., 2010; Brusius et al., 2013)
2. Identify the PSF and true image simultaneously (Kundur and Hatzinakos, 1996; Messaoud and Nouri, 2013).

2. Literature Review

Image quality assessment (IQA) metrics are used to automatically and robustly measure the image quality (Zhang et al. 2011). According to the availability of a reference image, objective IQA metrics can be classified as full reference (FR), no-reference (NR) and reduced-reference (RR) methods (Wang et al., 2004). Mean Square Error (MSE), Peak-Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are examples of reference based metrics.

Crete et al. (2007) proposed a no-reference blur detection method based on intentional blurring pixel difference (IBD). This method is inspired with the observation that the intentional blurring of a sharp image gives significant gray scale variations. This method fails to detect blur when the image has a smaller amount blurring effect. Narvekar and Karam (2011) presented a no-reference image blur metric that is based on the study of human blur perception for varying contrast values. This metric utilizes a probabilistic model to estimate the probability of detecting blur at each edge in the image, and then the information is pooled by computing the cumulative probability of blur detection (CPBD).

Yang et al. (2013) presented a no-reference image blur assessment using the feature of gradient profile sharpness (GPS). Bahrami and Kot (2014) proposed a simple and fast approach for no-reference image sharpness quality assessment. In this approach, the maximum local variation (MLV) of each pixel as the maximum intensity variation of the pixel with respect to its neighbours is used as a metric to measure sharpness.

While most previous work focuses on image deblurring, not as much research has been done on blur classification, which is more practical because the type of blurs is usually unknown in images. Multilayer neural network based on multi valued neurons (MLMVN) is used by Aizenberg et al. (2008) to identify both types and parameters of the point spread function. Yan and Shao (2013) made an attempt to find a general feature extractor for common blur kernels with various parameters, which is closer to realistic application scenarios and applied deep belief neural networks for discriminative learning.

Motion blur estimation requires identification of two parameters angle (θ) and length (L). The spatial domain methods are based on the observable fact of motion causing uniform smear tracks of the imaged objects. Yitzhaky and Kopeika (1996) illustrate that this smearing decreases the sharp features of image along the motion orientation, while it does not affect on the high frequency features in other directions. Accordingly, one can estimate the motion blur angle by differentiating the blurred image in all orientations and finding the direction where the total intensity of the image derivative is least. The estimation of the blur length in the spatial image domain is based on the observation that the derivative of a blurred image along the smear track emphasises the edges of the track which makes it possible to identify its length. However, this approach works at its best when the imaged objects are distinct from the background, so that the smears look like distinct tracks. It also assumes that the original image has similar local characteristics in all directions.

The motion blur direction identification is commonly done in the frequency domain. Wu et al. (2007) presented a motion blur estimation method based on cepstrum analysis of blurred image. This is based on the observation that the cepstrum of the motion blur point spread function has large negative spikes at a certain distance from the origin, which are preserved in the cepstrum of the blurred image. The blur parameters can be estimated using this information. However, this method delivers good results in the nonexistence of noise, because image noise suppresses the negative spikes caused by the blur.

The anisotropy in the spectrum of the blurred image can be used to determine the angle, which is perpendicular to the motion direction. Lokhande et al. (2006) have used Hough transform to detect the orientation of the lines in the spectrum treating it as an image and cepstrum transform to find blur length. The Radon transform delivers a two-dimensional array of line parameters in which the coordinate of the maximum value provides an estimate of the blur angle. According to Krahmer et al. (2006), the Radon transform delivers the most stable results. However, this method requires a large amount of computation time and storage space.

Dobes et al. (2010) have proposed a fast method of finding motion blur length and direction to reduce the computation time by computing the power spectrum of the image gradient in the frequency domain. They find orientation of motion blur using Radon transform and use the distance between the neighbouring stripes in power spectrum to estimate the blur length. Fang et al. (2011) proposed a method consisting of Hann windowing and histogram equalization as pre-processing steps before motion blur parameter estimation in frequency domain.

A method using Gabor filter for blur direction and radial basis function neural network for blur length with sum of Fourier coefficients as features to estimate the motion blur parameters presented by Dash et al. (2012). An efficient motion deblurring for barcode recognition on mobile devices by transforming the image into the frequency domain and computing its logarithmic power spectrum is presented by Brusius et al. (2013). This algorithm identifies the parameters describing the camera motion that caused the blur.

Kim et al. (1998) proposed a digital auto-focusing system which applies block based edge categorization to decide the defocus blur extent. This method fails in restoration of high frequency details because it works for the low and median frequencies. Wu et al. (2005) presented a method which analyzes line spread function to find the exact location of blur edges in spatial domain and then used this information for defocus parameter estimation. But in presence of noise it is difficult to find exact location of edges. A method based on histogram analysis of an edge image is presented by Lin and Chou (2012). In this method the histogram matching between the synthesized and real defocused regions is carried out with intensity-dependent filtering. By iteratively changing the point spread function parameters, the best blur extent is identified by the histogram comparison.

Addiati et al. (2009) have used cepstral information of blurred image to identify radius of the defocus blur. But this method show poor results in presence of noise. A method is proposed by Lee et al. (2010) has utilized cellular neural network (CNN) as regression tool with wavelet features. Chen et al. (2012) have estimated the defocus blur in frequency domain by using circular Hough transform. A method to estimate the defocus blur parameters for blind restoration of natural images based on the spectrum of the blurred images is suggested by Oliveira et al.

(2014). A modified radon transform is designed to identify the blur parameter by fitting an appropriate function that accounts separately for the natural image spectrum and the blur frequency response. This method shows effective results for natural blurred images but it is not suitable for other types of images.

Fabian and Malah (1991) proposed a method based on PSF to address the problem of simultaneously existing motion and out-of-focus blur in an image. The PSF models introduced by them is not able to efficiently and automatically select parameters, thereby directly affecting the effectiveness of the restoration and increasing the time needed to deblur the images. Therefore, Favaro et al. (2004) proposed an anisotropic diffusion model to solve the problem. However, their method is time consuming. Wu et al. (2006) proposed a method to estimate defocus blur parameter in joint blur with the assumption that PSF of motion blur is known. In this method a reduced and updated Kalman filter is applied for blurred image restoration where the best defocus parameter is estimated on the basis of maximum entropy.

Chen et al. (2008) presented a point spread function based approach in which a sharpness measure is employed as a cost function to automatically select optimal parameter values for PSF. Liu and Zhao (2011) solved the problem of combined blur parameters identification using radon transform and back propagation neural network.

After estimation of the blur parameters, an appropriate PSF can be calculated. This blur kernel then can be used to reconstruct an approximation of the original image from the distorted image using deconvolution methods such as Wiener filter and Lucy- Richardson (Brusius et al., 2013).

3. Research Motivations and Contributions

- In recent years, although various methods have been suggested for blind restoration of images, there is enough scope to improve their restoration performance.
- Most of the existing algorithms are based on statistics of natural images. But, they do not necessarily work well on barcode images which are quite different from normal images. So the barcode images need to be processed in a different manner.
- Motion and defocus blurs are the most common types of blur which are studied frequently for blind restoration. The investigation which considers the combined effect of both the blurs is rare due the inherent complexity in dealing with the same and therefore need to study in depth.
- It is necessary to identify the blur type before application of any blind restoration technique. A method which categorizes a blurred image into motion, defocus or combined blur does not exist. So, it explores the scope for designing of blur classification frameworks.
- In case of barcode scanning by digital camera, there may be a need of unified framework for restoration of blurred barcode images. Such a framework must be capable to detect the

blurred image and to recognize the blur type. After successful blur type recognition it must be capable to restore the image by application of blur restoration scheme corresponding to particular type of blur.

Keeping the aforesaid research motivations in view, an effort has been made in this work for blind restoration of the blurred barcode images. In particular, the thesis contributes by devising a unified framework for blind restoration of blurred barcode images which consists of objectives to

(i) design a novel blur detection scheme which can categorize sharp and blur barcode images.

(ii) propose a classification framework to categorize blur in motion, defocus and combined blur categories.

(iii) devise a novel algorithm to find motion blur parameter for effective image restoration.

(iv) propose a mechanism to find defocus blur parameter for efficient image restoration.

(v) design a method which can estimate blur parameters for simultaneous motion and defocus blurs.

(vi) application of suitable deconvolution algorithm to restore degraded barcode images with estimated blur parameter.

Figure 1.1 shows the different stages of blind restoration of blurred barcode images in unified framework.

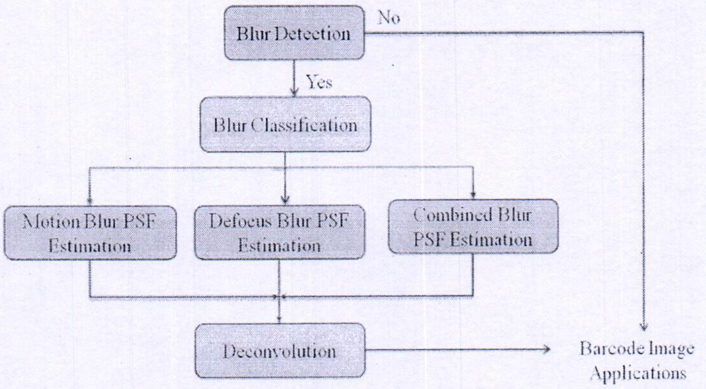
Blur Detection
No
Yes
Blur Classification
Motion Blur PSF Estimation
Defocus Blur PSF Estimation
Combined Blur PSF Estimation
Deconvolution
Barcode Image Applications

Figure 1.1: A unified framework for blind restoration of blurred barcode images.

4. Description of the research work

The work described in this thesis focuses on designing a unified framework that performs the blind restoration of blurred barcode images consisting of motion blur, defocus blur or combination of these two blurs. This framework detects presence of blur, identifies blur type in blurred image and performs blind restoration of blurred image. The whole framework consists of four main components: blur detection, blur classification, blur parameter estimation and deblurring. The performance of the proposed techniques has been evaluated using many camera based barcode images. To simulate the algorithms, two different barcode image databases are considered. The first database WWU Muenster Barcode Database (Wachenfeld et al., 2008) consisting of 1-D barcode images and the second one is the Brno Institute of Technology QR code image database (Szentandrási et al., 2012) captured by digital camera.

4.1 Blur Detection: The first component is designed to address the problem of blur detection. Three different approaches are presented for blur detection in barcode images. In the first two methods wavelet transform and local phase congruencies have been used to design the no-reference blur metric. In these methods, the main idea is to establish the degree of blurring caused by intentional blurred image, compared to the original image. This comparison allows to evaluate the relative blur effect between the two images. A greater variation among the original image and the intentional blurred image reveals that the original image is sharp. However, less variation indicates that the original image is already blurred.

In the third method, another no-reference blur detection scheme is presented which utilizes statistical features of local phase congruency map and gradient magnitude map. In this method, blur detection is achieved by approximating the functional relationship between these features and blur using a feed forward neural network. The statistical features provide information about the properties of the probability distribution. Statistical features of the phase congruency histogram and gradient magnitude histogram such as mean, standard deviation, smoothness, skewness, uniformity and entropy are computed by using the probability distribution of the different levels in the histogram bins of the histograms. A feed forward neural network is used to classify an image as a degraded or sharp one, separately with each feature set i.e. phase congruency statistical features (PCSF), gradient magnitude statistical features (GMSF) and hybrid features (HF).

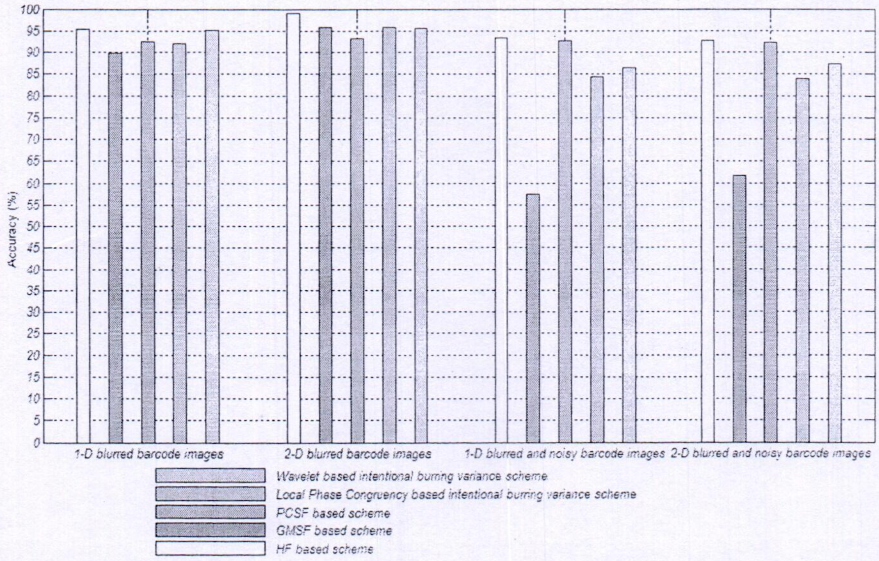

Figure 1.2: Comparative analysis of blur detection accuracies using wavelet based intentional blurring variance scheme, local phase congruency based intentional blurring variance scheme, PCSF based scheme, GMSF based scheme and HF based scheme.

Results achieved by all the blur detection methods are plotted in Figure 1.2. It is found that HF based blur detection scheme has the best discriminating ability between sharp and blurred images. In the first experiment of this approach which uses blurred 1-D and 2-D barcode images, the overall detection accuracies are 95.3% and 99.0% respectively. The second experiment of the same method which uses blurred and noisy 1-D and 2-D barcode images the overall blur detection accuracies are 93.3% and 92.7% respectively.

4.2 Blur Type Recognition: After successful blur detection, the second component of framework deals with blur classification. The motion blur, defocus blur are appeared differently in frequency spectrum, and the blur categorization can be easily done using these patterns. If the blurred image is transformed in frequency domain, it can be seen from frequency response of motion blurred image that the dominant parallel lines appear which are orthogonal to the motion blur orientation with near zero values. In defocused blur one can see appearance of some circular zero crossing patterns and in case of coexistence of both blurs combined effect of both blurs becomes visible. One can consider these patterns in frequency domain as image itself for blur classification.

Four different methods are designed which classify the blur into motion, defocus or combined blur categories. The first method uses statistical moments based features, the second method applies wavelet transform based features, and the third method uses ridgelet transform based features and the last method uses curvelet transform based features. In all the methods a multilayer feed forward neural network has been utilized as a classifier.

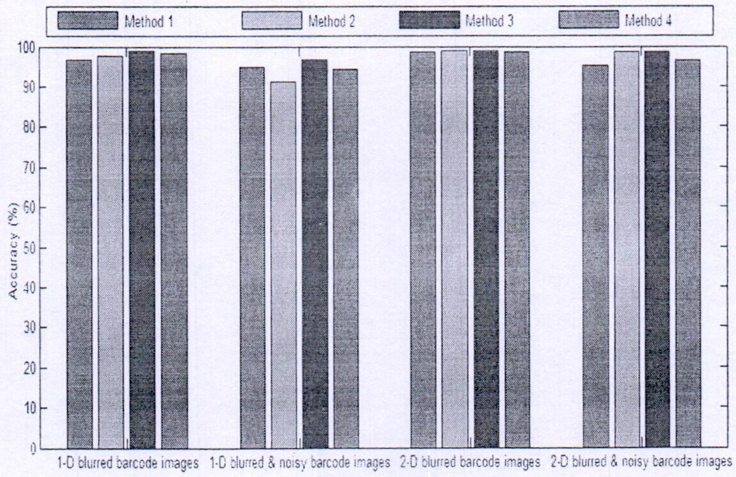

Figure 1.3: Comparative analysis of classification accuracies for four different blur classification schemes. Method 1 utilizes statistical moment based feature set, method 2 utilizes wavelet transform based feature set, method 3 utilizes ridgelet transform based feature set and method 4 utilizes curvelet transform based feature set for designing of the neural network model.

Comparing the results in graph of Figure 1.3, it is evident that the performance of the third method which utilizes ridgelet transformed based energy features is best over all other approaches. In the first experiment of this method which uses blurred 1-D barcode images, the overall classification accuracy is 99.0%. The second experiment which uses blurred and noisy 1-

D barcode images the overall classification accuracy is 96.8%. In the third experiment which uses blurred 2-D barcode images, the overall classification accuracy is 99.0%. The fourth experiment which uses blurred and noisy 2-D barcode images the overall classification accuracy is 98.7%.

4.3 Blur Parameter Estimation: The third component comprises of blur parameter estimation approaches which are required after blur type identification. This component of framework demands a separate approach for each class of blur due to the dissimilar natures of motion, defocus and combined blurs.

4.3.1 Motion Blur Estimation: A uniform motion blur parameters estimation approach using ridgelet transforms is designed. In this method, the energy of ridgelet coefficients is used to estimate the motion blur angle. Radial basis function neural network (RBFNN) using ridgelet transform based energy features has been utilized to estimate motion blur length. This approach gives 0.64 and 0.15 mean absolute errors in angle estimation with $L = 20$ for 1-D and 2-D blurred barcode images respectively. In presence of 40 dB BSNR noise errors are 1.97 and 0.27 for 1-D and 2-D blurred and noisy barcode images respectively. The mean absolute error (MAE) values are found near to zero for length estimation in all experiments with $\theta = 0$ degree. In presence of 40 dB noise errors are 0.18 and 0.14 for 1-D and 2-D blurred and noisy barcode images respectively. The main advantage of the suggested method is that it is more robust because ridgelet transform has an excellent high directional sensitivity and anisotropy for linear singularities in comparison to other directional filters.

4.3.2 Defocus Blur Estimation: Two different techniques for estimating the parameter of defocus blur are formed. These methods use ridgelet transform and curvelet transform to find the features of the defocus blurred images and utilize a radial basis neural network to estimate the blur parameter. These defocus blur parameter identification methods are based on the observation that blur induces distortion of image, which can be noticed as loss of high-frequency energy. It is revealed that this loss of energies can be mapped with blur parameter. Radial basis function neural network based model are designed using the energies of ridgelet and curvelet transformed images. It is shown that these models can serve as an identification of blur parameter. Ridgelet transform based approach gives 0.091 and 0.08 root mean square errors for 1-D and 2-D blurred barcode images respectively. In presence of 40 dB blurred signal-to-noise ratio, root mean square errors of this method are 0.5958 and 0.3633 for 1-D and 2-D blurred and noisy barcode images respectively. Curvelet transform based approach gives 0.3416 and 0.3178 root mean square errors for 1-D and 2-D blurred barcode images respectively. In presence of 40 dB BSNR, root mean square errors of this method are 0.4362 and 0.4219 for 1-D and 2-D blurred and noisy barcode images.

4.3.3 Combined Blur Estimation: A method based on logarithmic power spectrum analysis has been presented to identify the parameters of combined blur. In this method, an enhanced Radon transform has been used to identify blur angle and the blur length and blur radius of the combined blur are estimated with generalized regression neural network (GRNN). The input of GRNN is the sum of the amplitudes of the normalized logarithmic power spectrum along vertical direction and concentric circles for motion and defocus blurs respectively. Results show that proposed scheme for simultaneous blur parameter identification is very accurate. The mean absolute error for angle estimation for three cases $L = R$, and $L < R$ are found 1.33, 1.42 and 0.61 respectively for 1-D blurred images. In the experiment with 2-D blurred barcode images the mean absolute errors are achieved as zero for the first two cases and 0.14 for the third case. The MAE values are found near to zero for length and angle estimation in all experiments. Analysis of results also reveals that different ratios of blur extents do not alter the performance significantly. In future, this work can be extended by identifying parameters of the blurred image with noise interference.

4.4 Image Deconvolution: Finally, the last component is targeted to perform deblurring using the estimated blur parameters. Lucy-Richardson deconvolution algorithm has been utilized to deblur the blurred barcode images. The visual as well as the peak signal-to-noise ratio (in dB) of restored images are compared with maximum-likehood blind deconvolution method which shows the superiority of image restoration after proposed parameter estimation approaches.

5. Conclusion

A unified framework for blind restoration of barcode images has been designed which detects a blurred barcode image, finds blur type and performs blind restoration of that image. This framework can be used for three types of blurred barcode images namely motion blurred, defocus blurred and combined blurred. The use of such a structured framework both improves the quality of the restoration algorithms and extends the applicability of the mobile camera for decoding of barcodes.

Although the algorithms discussed in this work perform nicely, some further extensions are possible. The scope of this thesis has few boundaries, which however offer perspectives for future research. These limitations are related to noise and nature of the blur. In future, proposed framework can be extended by incorporating noise removal methods in the designed methods to handle the more noisy images and by considering few more kinds of blur such as Gaussian blur, and atmospheric turbulence etc.

6. List of Publications

1. Shamik Tiwari, V. P. Shukla, S. R. Biradar, Ajay Kumar Singh, *"Certain Investigations on Motion Blur Detection and Estimation"*, Proceedings of international conference on signal, image and video processing, IIT Patna, pp. 108-114, 2012.
2. Shamik Tiwari, V. P. Shukla, S. R. Biradar, Ajay Kumar Singh, *"Review of Motion Blur Estimation Techniques"*, Journal of image and graphics (JOIG), 1(4):176-184, 2013.
3. Shamik Tiwari, V. P. Shukla, S. R. Biradar, Ajay Kumar Singh, *"Texture Features based Blur Classification in Barcode Images," I.J. Information Engineering and Electronic Business,* MECS Publisher, *vol. 5, pp. 34-41, 2013.*
4. Shamik Tiwari, V. P. Shukla, S. R. Biradar, A. K. Singh, "*Blur Classification Using Wavelet Transform and Feed Forward Neural Network*", IJMECS, vol.6, no.4, pp.16-23, 2014.DOI: 10.5815/ijmecs.2014.04.03
5. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Wavelet Based Intentional Blurring Variance Scheme for Blur Detection in Barcode Images*", IJIGSP, vol.6, no.6, pp.43-49, 2014.DOI: 10.5815/ijigsp.2014.06.06
6. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Blur Classification Using Ridgelet Transform and Feed Forward Neural Network*", IJIGSP, vol.6, no.9, pp.47-53, 2014.DOI: 10.5815/ijigsp.2014.09.06.
7. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Defocus Blur Parameter Estimation in Barcode Images using Fast Discrete Curvelet Transform*", International Journal of Tomography & Simulation, CESER Publications, vol. 27 (3), 2014.
8. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Blur Parameters Identification for Simultaneous Defocus and Motion Blur*", CSI Transactions on ICT, Springer, vol. 2(1), pp.11–22, 2014. DOI 10.1007/s40012-014-0039-3.
9. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*A No-Reference Blur Detection Scheme Using Local Phase Congruency Map of Images*", International Journal of Signal Processing and Imaging Engineering, vol. 1, pp. 24-30, 2014.
10. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*A Blind Blur Detection Scheme using Statistical Features of Phase Congruency and Gradient Magnitude*", Advances in Electrical Engineering, Hindawi, vol. 2014, Article ID 521027, 10 pages, 2014. doi:10.1155/2014/521027.
11. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Blind Restoration of Motion Blurred Barcode Images using Ridgelet Transform and Radial Biases Function Neural Network*", under review (in third round) in Electronic Letters on Computer Vision and Image Analysis (ELCVIA).
12. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Blind Restoration of Defocus Blurred Barcode Images*", under review (resubmitted after minor revisions) in CSI Transactions on ICT, Springer.
13. Shamik Tiwari, V. P. Shukla, S.R. Biradar, Ajay Kr. Singh, "*Blur Classification Using Curvelet Transform and Feed Forward Neural Network*", under review in Advances in Computer Engineering, Hindawi.

7. Proposed Chapters

The thesis is structured into nine chapters as follows —

Chapter 1: Introduction

This chapter provides the introduction to area, problem definition, overview of previous work in the area of blind image restoration and layout of the thesis.

Chapter 2: Image Transforms and Neural Network

This chapter outlines the various image transforms and classifiers used in this work.

Chapter 3: Blur Detection

In this chapter, no-reference blur detection schemes are presented.

Chapter 4: Blur Classification

Approaches for blur classification are presented in this chapter to categorize blur in three categories namely motion, defocus and combined blur.

Chapter 5: Motion Blur Parameters Estimation

This chapter proposes a novel technique for estimating the parameters of uniform motion blur using ridgelet transform and radial basis function neural network.

Chapter 6: Defocus Blur Parameter Estimation

This chapter presents two different techniques for estimating the parameter of defocus blur based on ridgelet transform and curvelet transform.

Chapter 7: Combined Blur Parameters Estimation

An approach to identify the combined blur parameters in barcode images which are blurred simultaneously by motion and defocus blur is considered in this chapter.

Chapter 8: Image Deblurring

In this chapter, an analysis of the non-blind deconvolution has been presented.

Chapter 9: Conclusions and Future Work

This chapter outlines the concluding remarks and the scopes for further research.

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Faculty of Engineering & Technology, MUST

No. MUST/FET/2014-15 Dated 06.10.2014

Notice

A Pre-Synopsis Seminar presentation by Mr. Shamik Tiwari (En. No. 090754) is scheduled on 17.10.2014 at 3:30 p. m. in the conference room of the new FET building. All members of SRC are requested to attend the same.

(Prof. J. V. Desai)
Dean

Copy to:

1. Prof. J. V. Desai, Dean-FET or his nominee:	Chairman
2. Prof. V. P. Shukla	Supervisor
3. Prof. S. K. Lenka	Member-Internal
4. Dr. V. K. Agarwal	Member External
5. Mr. Shamik Tiwari	Ph.D.Scholar

Date: 30/09/2014

To,

The Chairman SRC,
Faculty of Engineering & Technology,
MITS, Lakshmangarh.

Sub: Student Research Committee –meeting-reg.

Dear Sir,

I am pleased to inform you that one of my research scholars Mr. Shamik Tiwari (090754) has finalized his Ph.D. research work as approved by the SRC report on Comprehensive Examination dated 20/08/2012.

I request you to kindly arrange a meeting of SRC to assess the work through pre-Synopsis Seminar as per clause R.18 (1)-(a) in Ordinances and regulations for Doctoral Programme, MITS-2006.

Prof. S.R. Biradar, a member of SRC in capacity of Co-Supervisor has also agreed to be present in the seminar.

To
Sushil
AO

Yours Sincerely
Shukla
Prof. Vidya Prasad Shukla
(Supervisor)

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Mody Institute of Technology & Science
(Deemed University under Section 3 of UGC Act, 1956)
LAKSHMANGARH – 332 311, Distt. Sikar, Rajasthan
Ph. : (01573) 225001 – 12 (12 Lines) Fax : (01573) 225041
E-mail : registrar@mitsuniversity.ac.in Website : www.mitsuniversity.ac.in

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Ref. No. M-2B **Dated:** 26.09.2012

To,
Mr. Shamik Tiwari
Research Student
Faculty of Engineering & Technology
Mody Institute of Technology & Science

Subject: Registration as Research Scholar

This is to certify that Mr. Shamik Tiwari (Enrolment No. 090754) has now been registered as a Research Scholar for Doctoral Programme in the Faculty of Engineering & Technology, Mody Institute of Technology & Science, Lakshmangarh as per recommendation of the Students' Research Committee dated **20.08.2012.**

We wish Mr. Shamik Tiwari success in his endeavour.

Registrar
26/09/12

CC to:
VC, MITS
Dean, FET

To
Sushil
Aw

27/08/2012

To

The Dean

FET-MITS

Sub: Request for Research Scholar status-reg.

Sir,

With reference to R.16, PageNo:14 of 'Ordinances and Regulations for Doctoral Programme', I have completed the Pre-PhD. course work and passed the Comprehensive Examination (Written and Oral). My research plan has been duly recommended and approved by the SRC. So I request you to kindly grant me the status of Research Scholar.

Thanking You,

Yours truly,

(Shamik Tiwari)

PhD. Student-EnrollmentNo: 090754

Enclosures:

1. Copy of Proforma V
2. Copy of Minutes of SRC Meeting held on 20/08/2012
3. Course work credentials
4. Foreign Language Credentials.

Registrar
for n.a. please
01/09/12

Mody Institute of Technology & Science

(A Deemed University u/s 3 of the U.G.C. Act, 1956)

Faculty of Engineering & Technology

LAKSHMANGARH-332311, Distt. Sikar (Rajasthan)
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Receipt No. 4928

Received from ~~Miss~~ Mr. Shamik Tiwari Date 31/8 201

AIEEE Rank/Other .... Year

B.Tech. / MCA / M.Tech. / Ph.D.

~~d/o~~ S/D Mr. Anand Tiwari CS&E / E&CE / E&EE / IT / ME / VLSI / [✓ CS] / SP / NS / NST / RE

Day Scholar/Boarder

Enrolment No. 090754

S.No.	Particulars	Amout Rs.	P.
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2.	Caution Money (Refundable)		
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ACCOUNTANT

PROFORMA - II

MODY INSTITUTE OF TECHNOLOGY & SCIENCE
Lakshmangarh - 332311, Dist. Sikar (Rajasthan)

PROGRESS REPORT OF Ph.D. SCHOLAR

Semester: Spring Session: 2011-12

PART - A: *(To be completed by the Research Scholar)*

1. Student's Name Shamik Tiwari 2. Enrolment No. 090754
3. Department Computer Science & Engineering 4. Date of Registration July 2010
5. Status: Full-Time ☐ Part-Time ☑ Sponsored ☐ Non-sponsored ☐
6. Date of Passing the Comprehensive Examination (if applicable) 20-08-2012
7. Topic of Research (in capital letters) (in English) A UNIFIED FRAMEWORK FOR BLIND RESTORATION OF BLURRED DOCUMENT IMAGES
8. Brief Report of the work for the period: From 01-01-2012 to 20-08-12

"([illegible]tain Investigation on Motion Blurr detection & estimation", Paper presented in conference at IIT, Patna.

9. Dates of Candidacy, if applicable
10. Any other information regarding work done Course Work Seminar completed (

2. Comprehensive Examination (Written & Oral) cleared.
3. Research Plan presentation over.

(Signature of Student)

Date 21/08/12

PART - B: *(Performance & Recommendation of the Department)*
Through Head of the Department

Period : From Jan, 2012 to Aug., 2012

(a) Performance: Satisfactory ☑ Unsatisfactory ☐

(b) Recommendation: The candidate is advised to go for publications in international journals and apply for research grants to government institutions.

(Prof. V. P. Shukla) (Prof. S. R. Biradar)
Supervisor (s)
8.9.2012 8/9/2012
Date

Chairman, SRC
(Prof. J. V. Desai)

8/9/12
Head of the Department
(Prof. Prerna K. V.)

Note : 1. Credits are earned if student obtains a B or a higher Grade.
2. Registration is Cancelled if student gets E or F grade in any one course.

FOR USE OF OFFICE ONLY

Part A checked and the above recommendations are submitted for approval of the Dean.

for Dealing Officer

Approved / ~~Not Approved~~

Signature of the Dean